Targets and Limits for Management of Fisheries:

A Simple Probability–Based Approach

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Abstract.—Precautionary fishery management requires that a distinction be made between target and limit reference points. We present a simple probability framework for deriving a target reference point in fishing mortality rate *F* or biomass *B* from the corresponding limit reference point. Our framework is a generalization of one devised previously.[1] Both methods require an a priori management decision on the allowable probability of exceeding the limit reference point; our new method removes a major assumption by accounting for uncertainty in the limit reference point. We present theory of the method, an algorithm for solution, and examples of its application. The new procedure, like the old, requires an estimate of implementation uncertainty expected in the following year's management, an estimate that might be obtained by a review of the effectiveness of past management actions. Either method can be implemented easily on a modern desktop computer. Our generalized framework is more complete and we believe that it has wide applicability in the use of fishery reference points, or for that matter in other conservation applications that strive for resource sustainability.

Copyeditor: We have included a citation in the abstract, as our work is a direct extension of the cited work. Although this differs from usual AFS style, C. Moseley advises an exception might be possible in this case. Thank you. —Authors.

[1]Caddy, J. F., and R. McGarvey. 1996. Targets or limits for management of fisheries? North American Journal of Fisheries Management 16:479–487.

In recent years, precautionary management of fisheries (e. g., FAO 1995) has become well established. In defining and implementing precautionary management, the concepts of *limit reference point* and *target reference point* have been found useful by scientists and managers (Smith et al. 1993; Mace 1994; Caddy 1998). These concepts were promoted by the United Nations Conference on Straddling Fish Stocks and Highly Migratory Fish Stocks (United Nations 1995) and the U.N. Code of Conduct for Responsible Fishing (Caddy and Mahon 1995). In simple terms, a limit reference point (LRP) reflects the perceived maximum degree of safe exploitation for a stock. It is implicit that an LRP should rarely be exceeded (Mace and Sissenwine 2002). Depending on the assessment and management techniques in use, an LRP can be expressed in terms of fishing mortality rate F, stock biomass B, spawning-stock biomass SSB, or other metrics of exploitation rate or stock abundance. (Symbols and abbreviations used in this paper are defined in Table 1.) A target reference point (TRP) uses the same metric as the corresponding LRP and defines the degree of exploitation aimed for under management. When reference points are measured in F, the preceding definitions imply that TRP < LRP; when reference points are in B or SSB, they imply that TRP > LRP. Stock assessment and management are uncertain, and the difference between TRP and LRP constitutes a margin of safety that prevents frequent excursions of exploitation beyond the LRP and thus promotes sustainability (Mace 2001).

In the United States, recent changes introduced by the Sustainable Fisheries Act have introduced a precautionary approach to fishery management at the federal level (Magnuson–Stevens Act Provisions 1998). Technical guidelines (Restrepo et al. 1998) issued to implement that act suggest methods for computing reference points in B and F and corresponding control rules. Thus, use of reference points in U.S. marine fishery management has become widespread and is likely to continue. In U.S. technical and regulatory documents, (e. g., Restrepo et al. 1998), LRPs are often called thresholds.

When establishing reference points, how one chooses among competing models is a very broad question, one whose answer will depend on the nature of the resource and the fishery. Here we explore a different, but nonetheless important, question: Given an LRP, how can the corresponding TRP be computed? Implicit in that question is the assumption that management can decide on a suitable TRP—e. g., F_{MSY} (the fishing mortality rate associated with maximum sustainable yield) or a minimum spawning-stock threshold—and that suitable assessment models can provide a working estimate of its value.

The Caddy–McGarvey Framework for Setting a TRP

One approach for computing a TRP corresponding to a specified LRP was provided by Caddy and McGarvey (1996), who based their argument on simple statistical theory. They assumed the TRP is the central tendency of a probability density function (pdf) that describes the uncertain outcome of a given set of management actions. They then showed that, if the shape of the pdf is known, the TRP can be calculated from an acceptable probability P^* of exceeding the LRP.

Caddy and McGarvey (1996) developed the mathematical representation of their methodology (which we denote as CM) using fishing mortality rate F as the management control variable. Ambiguously, they used the symbol F_{now} to refer to both the target reference point in F, which is a fixed number, and the current fishing mortality rate, which is a quantity estimated with uncertainty. Here we distinguish those two concepts by using F_τ to represent the target reference point and F_{next} for the realized fishing mortality rate in the management period, typically the next year. In our notation, the CM framework is represented as

$$\Pr(F_{\text{next}} > F_\lambda) = \int_{F_\lambda}^{\infty} \text{pdf}_{F_{\text{next}}}(F)\, dF = P^*, \tag{1}$$

where $\Pr(x)$ is the probability of condition x; F_λ is the limit reference point in F; and $\text{pdf}_{F_{\text{next}}}(F)$ is the pdf of F_{next} evaluated at F.

Caddy and McGarvey's assumption that $\text{pdf}_{F_{\text{next}}}(F)$ is centered on the TRP implies a belief that implementation of the TRP, although imprecise, is accurate. Consequently, when F_τ is increased or decreased, the probability $\Pr(F_{\text{next}} > F_\lambda)$ increases or decreases accordingly so that some particular value of F_τ provides the desired probability P^* (Figure 1).

Solution of CM Framework for TRP

The solution of equation (1) for F_τ is completed in two steps. First, one must specify the pdf of F_{next} and estimate or assume its parameters. Second, one must use a solution algorithm to find the value of F_τ corresponding to the desired P^*. If in the first step the pdf is normal or lognormal, then its location parameter (mean or median) will be based on F_τ and only its dispersion parameter (SD of F_{next} around F_τ) will remain to be specified. For example, if F_{next} is normally distributed with mean F_τ and standard deviation $\sigma_{F_{\text{next}}}$, equation (1) becomes

$$\Pr(F_{\text{next}} > F_\lambda) = \int_{F_\lambda}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_{F_{\text{next}}}} \exp\left(-\frac{(F - F_\tau)^2}{2\sigma_{F_{\text{next}}}^2}\right) dF = P^*. \tag{2}$$

In the CM framework, the acceptable probability level P^* has been established by managers; the LRP F_λ is assumed available from assessment results; and $\sigma_{F_{\text{next}}}$ is assumed estimable by some systematic or ad hoc method, as discussed later. The only unknown is the value of F_τ that will make the equation true.

To effect the second step of the solution, equation (2) can be solved for F_τ by evaluating the integral at successive trial values of F_τ until a value is found that satisfies the equation. The trial values are chosen in a systematic way; e. g., by the bisection method (Gill et al. 1981). Although the integral has no explicit solution, numerical methods of integration are easily within the capability of modern computers.

Because the integral in equation (2) must be evaluated numerically, finding the solution value of F_τ is an iterative process. A simpler approach is to use an approximation of the inverse–normal function Z^{-1} (e. g., Adams 1969). For a random variable $x \sim \mathrm{N}(0, 1)$, the inverse–normal function is defined

$$Z^{-1}(\pi) \equiv z \quad \text{such that} \quad \mathrm{Prob}(x < z) = \pi \tag{3}$$

Given the ability to compute the inverse–normal function, it is possible to compute the expected TRP directly as

$$F_\tau = \frac{F_\lambda}{1 + \mathrm{CV}_{F_{\mathrm{next}}} \cdot Z^{-1}(1 - P^*)} \quad . \tag{4}$$

Similarly, if F_{next} is lognormally distributed, one may compute the median TRP as

$$F_\tau = \frac{F_\lambda}{\exp\left[\sigma_{F_{\mathrm{next}}} \cdot Z^{-1}(1 - P^*)\right]} \quad . \tag{5}$$

In equation (4), we use the coefficient of variation (CV) of the TRP rather than its SD, but of course the two are interchangeable by the relationship CV = SD/mean. In a specific example of this approach, Caddy and McGarvey (1996) gave numerical approximations from which F_τ could be computed, assuming normal uncertainty in F_{next} and given $\sigma_{F_{\mathrm{next}}}$, F_λ, and P^*.

Generalization of CM for Uncertainty in Limit Reference Point

The CM approach is attractive for several reasons. Chief among them are that it recognizes uncertainty in the TRP; it is conceptually simple and thus easily communicated; and it is based on an explicit probability framework, rather than completely ad hoc reasoning. Importantly, specification of P^* by managers emphasizes the nonscientific dimension of setting a target.

The most obvious limitation of the CM framework is that it assumes zero variability in the LRP. That assumption is not realistic, because any estimate of a limit reference point (whether measured in F, B, or other metric) is derived from imprecise data and thus is imprecise itself. It is not difficult to generalize the preceding framework to account for imprecision in F_λ as well as in F_τ. The more general form of equation (1) is

$$\Pr(F_{\text{next}} > F_\lambda) = \int_{-\infty}^{\infty} \Pr(F_{\text{next}} > F) \cdot \Pr(F_\lambda = F)\, dF, \tag{6}$$

or equivalently,

$$\Pr(F_{\text{next}} > F_\lambda) = \int_{-\infty}^{\infty} \left[1 - \text{cdf}_{F_{\text{next}}}(F)\right] \cdot \text{pdf}_{F_\lambda}(F)\, dF, \tag{7}$$

where the cumulative distribution function $\text{cdf}_{F_{\text{next}}}(F)$ may require integration or numerical approximation. Equations (6) and (7) can be interpreted as summing weighted averages of the CM method across all possible values of F_λ, the statistical weights being the relative probabilities of observing that value of F_λ. The generalization assumes that uncertainty in F_{next} and uncertainty in F_λ are independent, an assumption that is relaxed later.

We illustrate our generalized framework using two hypothetical examples that differ only in location parameter (mean or median) of the TRP (Figures 2 and 3). The figures parallel equation (7): in each figure, the uppermost plot shows $1 - \text{cdf}_{F_{\text{next}}}(F)$, the center plot shows $\text{pdf}_{F_\lambda}(F)$, and the lowermost plot shows the product of the two, i. e., the full integrand in equation (7). Area under the lowermost curve is $\Pr(F_{\text{next}} > F_\lambda)$. Comparison of the two figures reveals that, as expected, the probability of exceeding the LRP becomes lower as the TRP is reduced from $F_\tau = 0.4$ (Figure 2) to $F_\tau = 0.3$ (Figure 3). A similar reduction would occur if the LRP were made higher or the SD of either the TRP or LRP were reduced.

When statistical distributions for F_{next} and F_λ are known or estimated, equation (7) can be written in a more explicit form. Assuming normal distributions, for example, the new equation is

$$\Pr(F_{\text{next}} > F_\lambda) = \frac{1}{2\pi\sigma_{F_{\text{next}}}\sigma_\lambda} \int_{-\infty}^{\infty} \left[\int_{F}^{\infty} \exp\left(\frac{(\phi - F_\tau)^2}{2\sigma^2_{F_{\text{next}}}} \right) d\phi \right] \exp\left(\frac{(F - F_\lambda)^2}{2\sigma^2_\lambda} \right) dF \qquad (8)$$

where $\sigma_{F_{\text{next}}}$ is the standard error of F_{next}, and σ_λ is the standard error of F_λ. Given a value of P^* chosen by managers and estimates of $\sigma_{F_{\text{next}}}$, σ_λ, and F_λ, equation (8) can be solved for F_τ. The double integral here can be more time-consuming to compute than the single integral in equation (2), and the possibility of a direct solution based on an approximation for Z^{-1} is no longer available (although approximation of Z^{-1} for the inner integral can be used to speed the computations). The only additional data requirement of the generalized framework is an estimate of σ_λ.

With minor adjustments, the same approach can be used for lognormally distributed uncertainty. It can also be adapted to other continuous distributions, as long as their density and distribution functions can be characterized from the information at hand and then evaluated analytically or numerically.

For simplicity, we have assumed above that uncertainties in F_{next} and F_λ are independent. That assumption is convenient, but not necessary. It is possible that the two quantities are correlated, as they are estimated from the same data and assessment framework. In that case, one could estimate the joint probability density of F_{next} and F_λ

(e. g., a bivariate normal distribution) and integrate it over the appropriate region. We suspect, however, that in practice correlation between the two quantities will be low owing to the large implementation uncertainty in F_{next}, which is quite separate from the estimation uncertainty involved in finding F_{λ}, and that as a consequence, equation (7) will be applicable. We next present an approach that further reduces the possibility of correlation between F_{next} and F_{λ}.

Ratio–Extended Probability Approach to Setting Targets (REPAST)

From the generalized framework described above, we now develop a variant that appears well suited to application in fishery management, while avoiding the main source of correlation between F_{next} and F_{λ}. Because this variant is based on dimensionless quantities that can be written as ratios, we call it REPAST, for Ratio–Extended Probability Approach to Setting Targets. The REPAST framework was developed while considering properties of F_{MSY} as estimated from surplus–production models, and we explain it in that context. Nonetheless, we believe that analysts will find it applicable to other LRPs and assessment procedures as well.

As in many quantitative problems, progress can be made by replacing important variables with related dimensionless (scale-independent) quantities (Barenblatt 1996). In fishery science, the scale-independent approach has been used, for example, in developing the concept of spawning potential ratio (Goodyear 1993). Estimates of population state B_t and F_t at time t from a surplus–production model are more precise when expressed as dimensionless proportions of B_{MSY} and F_{MSY}, respectively, rather than in specific units of mass and time^{-1} (Prager 1994). In dimensionless form, the estimates no longer incorporate information on the catchability coefficient q, which is often poorly estimated. Indeed, determining the exact scale of a population (equivalent to determining q) is one of the most difficult problems in population dynamics (Smith 1994). An additional reason for preferring the dimensionless estimates is that the effects of bias and error in the sampling program will tend to cancel. For example, if only a consistent fraction of the population is sampled, the usual (scaled) estimate of B_t will be biased, but the dimensionless estimate will be unaffected.

It follows that the limit reference point F_λ, in this context equated to F_{MSY}, can be expressed with greater precision as a ratio to current (final-year) fishing mortality rate than it can be in absolute terms. We designate that ratio R_λ, defined here as $R_\lambda = F_{\text{MSY}}/F_{\text{now}}$ and more generally as $R_\lambda = F_\lambda/F_{\text{now}}$. The quantity R_λ is a dimensionless LRP, known with statistical error. It should be a routine matter to estimate R_λ from an assessment model, and almost as routine to obtain an estimate of its standard error or coefficient of variation.

Management of fishing mortality rate is also usually effected in a relative sense (as is management based on total stock biomass). By that, we mean that target fishing mortality rate in the next period F_τ is generally set by proportional adjustment to the current fishing mortality rate F_{now}, rather than by some totally new analysis of fishing power, fishing effort rate, etc. For the desired adjustment, we use the notation R_τ, defined such that $F_\tau = R_\tau \cdot F_{\text{now}}$. Thus the quantity R_τ is a dimensionless TRP, taking the form of a multiplier that will be implemented with statistical error. We assume as before that the multiplier actually achieved, R_{next}, is uncertain and can be described by a pdf centered on the desired TRP R_{τ}. Despite the transformation into dimensionless quantities, the method of attack remains the same. Computing the probability that $F_{\text{next}} > F_{\lambda}$ is essentially the same as computing the probability that $R_{\text{next}} > R_{\lambda}$. Equation (7) becomes

$$\Pr(R_{\text{next}} > R_{\lambda}) = \int_{-\infty}^{\infty} \left[1 - \text{cdf}_{R_{\text{next}}}(R)\right] \cdot \text{pdf}_{R_{\lambda}}(R)\,dR, \tag{9}$$

which can be solved for the value of R_{τ} that will produce the allowable probability P^* that $R_{\text{next}} > R_{\lambda}$. The solution is possible when pdf of R_{next} and pdf of R_{λ} are known or estimated. As with the CM method, any distributions can be specified, including empirical distributions.

Although conceptually REPAST is almost identical to our non-ratio-based generalization, there are two advantages of using dimensionless reference points. First, uncertainty in the dimensionless quantities should generally be less than in the original reference points, because the problem of scaling the population is avoided. Second, correlation between uncertainty in achieving the target and uncertainty in estimating the LRP is greatly reduced. As mentioned above, even the scaled quantities F_{next} and F_{λ} should be uncorrelated, because their major uncertainties stem from independent processes; uncertainty in F_{next} largely reflects imperfect implementation of regulations, while uncertainty in F_{λ} reflects estimation and sampling error. In practice, however, error in the two quantities will be correlated if there is an overall bias to the sampling regime. In contrast, uncertainty in the dimensionless quantity R_{next} depends only on implementation, not on sampling, and thus R_{next} will be uncorrelated with R_{λ}—except, perhaps, to the degree that compliance with regulations is correlated with their severity.

Whether the calculations are done in terms of scaled or dimensionless reference points, the best method of characterizing implementation uncertainty is not obvious. An ad hoc approach might be to postulate a provisional value by assuming a CV on R_{next}. A more empirical approach would be to estimate uncertainty from data on past performance of the fishery. By analyzing past intended management of F and results obtained, it should be possible to estimate the CV of R_{next}. An example of data-based modeling of such partial management control of a wild population is provided by Johnson et al. (1997).

Examples

Three examples follow. The first demonstrates the similarities and differences between the CM procedure and REPAST. The second and third apply REPAST to swordfish *Xiphias gladius* in the north Atlantic Ocean; in these examples, TRPs in fishing mortality rate and biomass are based on estimates, from a surplus–production model, of the CV of F_{MSY}. The applications to swordfish are intended strictly as examples and do not provide definitive information on that stock.

Example 1—Comparison to Caddy–McGarvey Procedure

In this example, we reexamine a case given in Caddy and McGarvey (1996) and recompute it using the REPAST generalization. The example is based on three assumptions: (1) The dimensionless limit reference point $R_\lambda = F_\lambda / F_{\text{now}} = 0.6$. That is, present fishing mortality rate is higher than the established LRP by the factor $1/0.6 \approx 1.67$. (2) Implementation of the dimensionless target reference point R_τ is uncertain and characterized by the CV of R_{next}. (3) To make our numerical results directly comparable to the example of Caddy and McGarvey (1996), we assume $F_{\text{now}} = 1.0/\text{yr}$. In that case, by definition $F_\lambda = R_\lambda/\text{yr}$ and $F_\tau = R_\tau/\text{yr}$.

If R_λ is specified as a point value, the example is the same as that of Caddy and McGarvey (1996). Resulting values of the target reference point R_τ are given in Table 2 for a range of P^* and CV of R_{next}. That table is more detailed than Table 1 of Caddy and McGarvey (1996) and also corrects an apparent error, their value of $F_\tau = -0.04/\text{yr}$ for $P^* = 0.05$ and CV= 1.00, but otherwise displays the same values.

We next assume, more realistically, that the dimensionless LRP R_λ is estimated with error (CV = 0.25), and we use REPAST to compute R_τ accordingly. The result is a slightly lower target at each combination of P^* and CV of R_{next} (Table 3). The values of R_τ are perhaps most informative when presented as a contour plot (Figure 4 a–b), as are the difference between procedures (Figure 4 c–d). Those differences are largest when CV of R_{next} is low, because then uncertainty in the limit reference point R_λ becomes more important.

Example 2—North Atlantic Swordfish

In this example, we apply REPAST to results from a surplus–production model, using F_{MSY} as the limit reference point (Mace 2001). Prager (2002) examined several aspects of production modeling of swordfish in the north Atlantic Ocean, based on catch and relative-abundance data for 1950–1998. Prager's analysis using a trimmed least-squares fit of the generalized production model provides an estimate of $R_\lambda = F_{MSY}/F_{1998} = 0.814$. We repeated that production–model analysis, adding a bootstrap, as in Prager (1994), to generate an empirical sampling distribution of R_λ (Figure 5). That distribution implies a variability around R_λ of CV = 0.263. Because the normal distribution appears a good approximation (Figure 5), we assume normality for this example.

Using $R_\lambda = 0.814$ with CV = 0.263, we solve equation (9) for the TRP over a range of P^* and CV of R_{next} (Figure 6). For example, at $P^* = 20\%$ and CV = 0.25, the TRP is $R_\tau = 0.60$, meaning that the appropriate target fishing mortality rate in the next period is 60% of current F. In general, with lower P^* or higher CV of R_{next}, the value of R_τ decreases.

Example 3—Reference Point in Biomass

This example is based on the same surplus–production model of swordfish, but differs by considering reference points in stock biomass, rather than in fishing mortality rate. For the sake of the example, we assume that the LRP in biomass is $B_\lambda = 0.75B_{MSY}$, the value suggested as a possible minimum stock-size threshold in Restrepo et al. (1998). We use the same notation as before, but here $R_\lambda = B_\lambda/B_{\text{now}}$ and $B_\tau = R_\tau \cdot B_{\text{now}}$, the distinction between dimensionless reference points in biomass and those in fishing mortality rate being clear from context. The point estimate of R_λ in biomass from the production model is 1.06, while in this case the bootstrap distribution of R_λ is characterized by a CV of 0.189. Again, the distribution appears close to normal (Figure

7), so the normal assumption is used in applying REPAST. Because of the change in reference points from F to B, the following replaces equation (9):

$$\Pr(R_{\text{next}} < R_\lambda) = \int_{-\infty}^{\infty} \left[\text{cdf}_{R_{\text{next}}}(R)\right] \cdot \text{pdf}_{R_\lambda}(R)\,dR. \tag{10}$$

The important point is the reversed inequality on the left-hand side of the new equation, reflecting TRP > LRP when the reference is biomass.

As with the previous example, results are presented as a contour plot (Figure 8). We choose the same point to exemplify the results; namely, $P^* = 20\%$ and CV = 0.25. The estimate is that, given the stated LRP, the target must be at least 140% of B_{now} (Figure 8). In general, R_τ increases with lower P^* or higher CV of R_{next}.

Discussion

We have described a simple framework for computing target reference points from limit reference points, a framework based on the work of Caddy and McGarvey (1996) but incorporating two major extensions. First, it allows for uncertainty in estimation of the limit reference point, and thus provides a more accurate picture of reality than the old procedure. Because the magnitude of that uncertainty can be estimated routinely by modern assessment models, the added data burden for this extension is small. Because that uncertainty is not assumed negligible, targets figured by the new procedure are somewhat more conservative than from the old procedure.

The second refinement is casting our framework in terms of dimensionless indicators of stock status. While at first that approach may seem more complex, we believe that it has advantages. It recognizes that management is usually applied by adjusting present fishing regimes; it takes advantage of the cancellation of sampling errors in estimated quantities, thus improving precision; and it reduces concern about the possible correlation of errors in the LRP and the realized target. By increasing precision, the use of dimensionless quantities may allow higher exploitation rates than a similar procedure using scaled values.

The disadvantages of our new procedure are that it is slightly more difficult conceptually than the original and that the computations are a bit more complex. We hope that our explanations have mitigated the first disadvantage and that free availability of software for the procedure (explained below) will mitigate the second.

Statistical Issues

A potential concern about dimensionless reference points is that, as ratios, they may have undesirable statistical properties. Indeed, the ratio of a constant to a normally distributed random variable (for example) has a $\bigcup$-shaped distribution that would be unsuitable for use with REPAST. Furthermore, it is frequently recommended that proportions, another type of ratio, be transformed before analysis (Snedecor and Cochran 1980). In contrast, ratio estimates are recommended as more precise than estimates of individual quantities when correlation between numerator and denominator of the ratio is high (Snedecor and Cochran 1980), as it should be in the ratios $R_\lambda \equiv F_\lambda / F_{\text{now}}$ and $R_\tau \equiv F_\tau / F_{\text{now}}$. For example, ratio estimators are recommended by Snedecor and Cochran (1980, p. 456) for estimating relative population sizes over time, a use reportedly introduced by Laplace in the early 1800s (Rao 1986). Thus, the use of dimensionless quantities (ratios) in REPAST appears statistically well founded. In addition, we note that the basic equations of surplus–production models involve not biomass itself, but biomass as a dimensionless ratio to carrying capacity (e. g., Fletcher 1978; Prager 1994; Quinn and Deriso 1999). For a fixed production–model shape (i. e., a fixed exponent in the generalized production equation), that is fundamentally the same dimensionless approach we have taken. In that sense, dimensionless estimates are more fundamental products of production models than the corresponding scaled estimates. As noted above, scaling is a major source of uncertainty even in more complex population models (Smith 1994).

When the CV of F_{next} is relatively large, as in the first example, and variability is assumed to be distributed normally, a noticeable portion of the distribution of F_{next} may lie below zero. There are two strategies for responding to this situation. One can either assume that all negative values of F_{next} are equivalent to $F = 0$, or one can renormalize the portion of the density function over the range $0 < F < \infty$ so that its integral is unity. The value of the TRP provided by our methods will depend on which strategy is used. In our examples, we used the first strategy, but we have no strong preference for one or the other. We do think that once a choice is made, it should be maintained in future assessments of the stock. We view the value of our methods not as providing TRPs that precisely match the chosen $P*$, but rather as providing repeatable, objective, statistically based TRPs that approximate the chosen $P*$. If neither strategy is acceptable, the entire issue can be avoided by using the equations for lognormally distributed uncertainty.

Reference Points in Biomass

The examples illustrate a structural difference between reference points in biomass and those in fishing mortality rate. In the latter, the LRP is often set at an estimate of (or proxy for) F_{MSY}, and for that reason, the nearer the applied fishing mortality is to the LRP, the higher the sustainable yield. The REPAST procedure provides in that sense an optimal fishing mortality rate within the constraints of $P*$. The LRP in biomass, in contrast, is usually set lower than B_{MSY}. Driving stock levels as near as possible to such an LRP would be a risk–prone approach that also reduced the sustainable yield. Therefore, we suggest that when using REPAST to compute reference points in biomass, the TRP be set to the computed value only if it would result in $B_{\tau} \geq B_{\mathrm{MSY}}$, to B_{MSY} otherwise.

The application of the CM approach or our generalizations of it to biomass–based TRPs is subtly different from its application to F–based TRPs in that biomass is not directly controlled by managers. Except where stocking is used, managers can increase the population only indirectly, by implementing rules to reduce F, and thus provide a larger stock biomass at some future time. This implies an added source of uncertainty, associated with the time it takes for the biomass to increase to the reference point. In principle, this aspect of the problem could be made transparent to managers through a model of the added uncertainty; such a model would describe the probability density of achieving B_{λ} (or R_{λ}) within a prescribed time.

Setting P^*

As noted by Shotton (1993), the probability P^* of exceeding the limit reference point acceptable to managers will depend on their aversion to risk. If relatively risk prone, they may choose, e.g., $P^* > 0.1$ for use with these methods. If more risk averse, they will tend to choose a lower probability of exceeding the LRP. Whatever the case, P^* is not a result, as in many approaches, but instead must be specified a priori to arrive at a target. We believe it is important that specification of this probability be recognized for the political (i.e., management) decision it is, and neither relegated to science, which cannot answer it, nor swept under the rug. Thus, we view the need to set P^* explicitly and a priori as a strength of the methods described here.

It is possible, nonetheless, that science can aid managers in determining a value of P^* that is optimal in some sense. Formal risk analysis provides a framework for quantifying risk, defined in that context as the mathematical expectation of loss from a policy. Thus, computer simulation of the stock's biology, management, and fishery could be used to calculate the risk (in that sense) associated with any value of P^*, and the value of P^* with lowest risk could be considered optimal. Such an approach is quite objective, yet it does not completely eliminate the subjective nature of setting P^*, as it makes necessary placing values on socioeconomic events such as fishery closures, changes in catch per effort, greater or lesser variability of annual catch, and recreational and aesthetic factors. Nonetheless, the focus of such a procedure is quite different from setting P^* empirically, and the approach could be useful, given the economic data and assumptions needed.

Reference Points, Implementation, and Data Collection

Application of CM or REPAST is in essence a control rule, in the sense of Restrepo et al. (1998), for management of fisheries. Like other approaches in which added precision in estimates of stock status yields a smaller margin between target and limit, use of REPAST makes evident the returns expected from expenditures on collecting relevant data (whether fishery-dependent or fishery-independent), because the quality of data will determine the variance in the estimation of the LRP used. As noted by Caddy and McGarvey (1996), an important consequence of this is that with a higher level of expenditure on monitoring, the same probability of exceeding the limit reference point occurs at a slightly higher rate of fishing than under the higher variability in LRP coming from less intensive monitoring. This makes explicit what was only implicit previously, namely that statistical monitoring has an economic value to the fishing industry. Similarly, the value of enforcement and compliance become more apparent, as they serve to reduce implementation uncertainty (variability in R_{next}), which also can reduce the required margin between target and limit.

The methods described here (including the CM method) assume explicitly that a target, once adopted, will be met on average. Experience suggests, however, that quotas (e. g.) are much more likely to be exceeded than underrun. From the scientific perspective, there is no reason that the statistical distribution of F_{next} must be centered on the target, as we have assumed. Any of the methods described can easily accommodate distributions centered at any point. Therefore, any of the methods is easily extended to allow for expected overruns. In such applications, the central tendency and dispersion of F_{next} or R_{next} might be estimated from data on performance of the fishery, as we suggested that the dispersion alone might be. In applying such estimates, it might be desirable to use a running average of (e. g.) the last few years' performance, so that changes in implementation effectiveness would be reflected in the new targets.

Application in Management

How can methods like REPAST best be used in ongoing fishery management? We suggest that they must be applied repeatedly, because monitoring and assessment techniques change over time, as does the status of the stock itself. The limit reference point is most usefully set as a theoretical quantity, e. g., F_{MSY}, rather than as a specific value of F or B, as formalizing a specific number often leads to difficulties when assessment methods change, or even as knowledge about the stock increases. The acceptable probability $P*$ of overshooting the LRP can also be established before assessment takes place. For application of REPAST, stock assessment results should include estimates of the relative LRP and its CV. A complementary analysis of the fishery's past performance can be used to estimate implementation uncertainty in management measures (e. g., uncertainty in F_{next}). From those estimates, REPAST is used to compute a relative TRP for the following period. The time of assessment would also be an excellent time for bioeconomic analyses, based on REPAST, of costs and benefits of reducing uncertainty. The possible extra yield from reduced estimation uncertainty is balanced against costs of better stock monitoring and assessment, which lower variability in the LRP, and against costs of better enforcement and fishery monitoring, which lower variability in implementing the TRP. In summary, at each assessment cycle, REPAST allows the computation of targets from stock and fishery status, and the opportunity to balance possible larger yields against the costs needed to attain them.

It is a property of all estimation schemes for fish and wildlife conservation, including estimates of reference points, that they are merely advisory. Remedial action, if needed, must be undertaken by other means: law, regulation, or other agreement. The value of reference points, it seems to us, is in establishing a framework within which such agreements can be made and, in the case of the methods proposed here, a logical method for determining the magnitude of adjustments that can be agreed upon. Thus such methods, if accepted with some fidelity, seem capable of furthering conservation management considerably.

Software

The authors have developed Fortran software implementing the REPAST scheme. Software, including source code, will be made available freely to colleagues requesting it. For software, contact M. H. Prager by email: `mike.prager@noaa.gov`.

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TABLE 1.— Abbreviations and mathematical symbols.

Symbol	Description
CM	Method of Caddy and McGarvey (1996) for finding a TRP from a precise LRP
CV	Coefficient of variation; standard deviation divided by mean
REPAST	Our method (extension of CM) for finding a TRP from an imprecise LRP
LRP	Limit reference point, in general
MSY	Maximum sustainable yield
TRP	Target reference point, in general
pdf	Probability density function
cdf	Cumulative distribution function (integral of pdf)
F	Instantaneous rate of fishing mortality
B	Biomass of stock
F_λ, B_λ	Value of F or B chosen to implement LRP
F_τ, B_τ	Value of F or B chosen to implement TRP
F_{now}, B_{now}	Estimated F or B at the close of the last observed period (typically, year just ended)
F_{next}, B_{next}	Realized F or B in the management period (typically, next year)
F_{MSY}, B_{MSY}	Value of F or B at which MSY can be realized
R_λ	LRP in F or B expressed relative to F_{now} or B_{now}
R_τ	TRP in F or B expressed relative to F_{now} or B_{now}
$P*$	Allowable probability of exceeding LRP in next management period
ϕ	Dummy variable used in double integration
σ_λ,$\sigma_{F_{\text{next}}}$	Standard error of LRP, standard error of TRP

TABLE 2.— Example with unitless limit reference point $R_\lambda = F_{MSY}/F_{now} = 0.6$, using CM method ($R_\lambda$ assumed precise). Values are of unitless target reference point R_τ that provide specified probabilities P^* of exceeding LRP in next period, as a function of CV of R_{next}. Abbreviations and symbols are defined in Table 1.

	CV of R_{next}									
P^*	0.05	0.10	0.15	0.20	0.25	0.33	0.50	0.66	0.80	1.00
Normal distribution of uncertainty—values are means										
50%	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
40%	0.59	0.59	0.58	0.57	0.56	0.55	0.53	0.51	0.50	0.48
35%	0.59	0.58	0.57	0.56	0.55	0.53	0.50	0.48	0.46	0.43
30%	0.58	0.57	0.56	0.54	0.53	0.51	0.48	0.45	0.42	0.39
25%	0.58	0.56	0.54	0.53	0.51	0.49	0.45	0.42	0.39	0.36
20%	0.58	0.55	0.53	0.51	0.50	0.47	0.42	0.39	0.36	0.33
15%	0.57	0.54	0.52	0.50	0.48	0.45	0.40	0.36	0.33	0.29
10%	0.56	0.53	0.50	0.48	0.45	0.42	0.37	0.33	0.30	0.26
5%	0.55	0.52	0.48	0.45	0.43	0.39	0.33	0.29	0.26	0.23
Lognormal distribution of uncertainty—values are medians										
50%	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
40%	0.59	0.59	0.58	0.57	0.56	0.55	0.53	0.52	0.50	0.49
35%	0.59	0.58	0.57	0.56	0.55	0.53	0.50	0.48	0.46	0.44
30%	0.58	0.57	0.55	0.54	0.53	0.51	0.47	0.44	0.41	0.39
25%	0.58	0.56	0.54	0.52	0.51	0.48	0.44	0.40	0.37	0.34
20%	0.58	0.55	0.53	0.51	0.49	0.46	0.40	0.36	0.33	0.30
15%	0.57	0.54	0.51	0.49	0.46	0.43	0.37	0.32	0.29	0.25
10%	0.56	0.53	0.50	0.47	0.44	0.40	0.33	0.28	0.24	0.21
5%	0.55	0.51	0.47	0.43	0.40	0.35	0.28	0.22	0.19	0.15

TABLE 3.— Example with unitless limit reference point $R_\lambda = F_{MSY}/F_{now} = 0.6$, using REPAST method with 25% CV of R_λ. Values are of unitless target reference point R_τ that provide specified probabilities $P*$ of exceeding LRP in next period, as a function of CV of R_{next}. Abbreviations and symbols are defined in Table 1.

	CV of R_{next}									
$P*$	0.05	0.10	0.15	0.20	0.25	0.33	0.50	0.66	0.80	1.00
	Normal distribution of uncertainty—values are means									
50%	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
40%	0.56	0.56	0.56	0.55	0.55	0.54	0.52	0.51	0.49	0.47
35%	0.54	0.54	0.53	0.53	0.52	0.51	0.49	0.47	0.45	0.43
30%	0.52	0.52	0.51	0.51	0.50	0.48	0.46	0.43	0.41	0.38
25%	0.50	0.49	0.49	0.48	0.47	0.46	0.42	0.40	0.37	0.35
20%	0.47	0.47	0.46	0.45	0.44	0.43	0.39	0.36	0.34	0.31
15%	0.44	0.44	0.43	0.42	0.41	0.39	0.36	0.33	0.30	0.28
10%	0.41	0.40	0.39	0.38	0.37	0.36	0.32	0.29	0.27	0.24
5%	0.35	0.35	0.34	0.33	0.32	0.30	0.27	0.24	0.22	0.20
	Lognormal distribution of uncertainty—values are medians									
50%	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
40%	0.56	0.56	0.56	0.55	0.55	0.54	0.52	0.51	0.50	0.48
35%	0.54	0.54	0.54	0.53	0.52	0.51	0.49	0.47	0.45	0.43
30%	0.53	0.52	0.52	0.51	0.50	0.49	0.45	0.43	0.41	0.38
25%	0.51	0.50	0.49	0.48	0.47	0.46	0.42	0.39	0.36	0.33
20%	0.49	0.48	0.47	0.46	0.45	0.43	0.38	0.35	0.32	0.29
15%	0.46	0.46	0.45	0.43	0.42	0.39	0.35	0.31	0.28	0.24
10%	0.43	0.43	0.41	0.40	0.38	0.36	0.30	0.26	0.23	0.20
5%	0.40	0.39	0.37	0.36	0.34	0.31	0.25	0.21	0.18	0.14

Figure Captions

Figure 1. Diagram of CM procedure, showing relationship of limit reference point F_{λ}, assumed variability of F_{next}, allowable probability P^* that $F_{\text{next}} > F_{\lambda}$, and resulting target reference point F_{τ}. Abbreviations and symbols are defined in Table 1.

Figure 2. Diagram 1 of generalized procedure, showing graphically the relationship of terms in equation (7). Coefficient of variation of TRP and of LRP are 25%. Abbreviations and symbols are defined in Table 1.

Figure 3. Diagram 2 of generalized procedure. Same as previous figure except that TRP has been reduced. Note reduced probability that $F_{\text{next}} >$ LRP. Abbreviations and symbols are defined in Table 1.

Figure 4. Panels (a) and (b): contours of R_{τ}, dimensionless target reference point in F expressed as a proportion of current F. Contours depend on allowable probability P^* of exceeding R_{λ}, the dimensionless limit reference point in F; value of R_{λ} (x–axis); estimated mean and CV of R_{λ} (here assumed 0.6 and 0.25, respectively); and CV of R_{next} (y–axis). Panel (a) assumes normal, and panel (b) lognormal, uncertainty. Panels (c) and (d): corresponding increase in estimates of R_{τ} when using procedure of Caddy and McGarvey (1996), which disregards uncertainty in estimation of R_{λ}. Abbreviations and symbols are defined in Table 1.

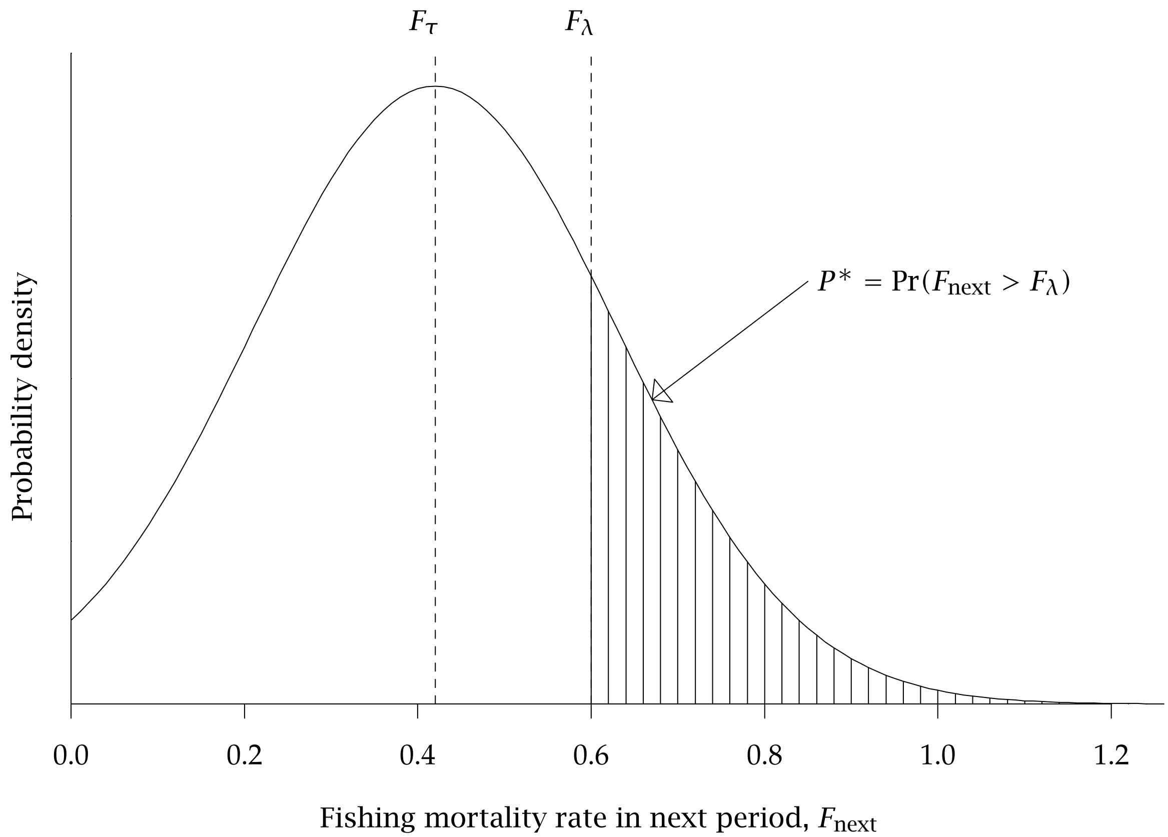
Figure 5. Solid line: empirical probability density of $R_{\lambda} = F_{\text{MSY}}/F_{\text{now}}$ from bootstrap fit

of generalized production model to trimmed data on swordfish in north Atlantic Ocean. Dashed line: normal probability density with equal mean and SD, shown for comparison. Abbreviations and symbols are defined in Table 1.

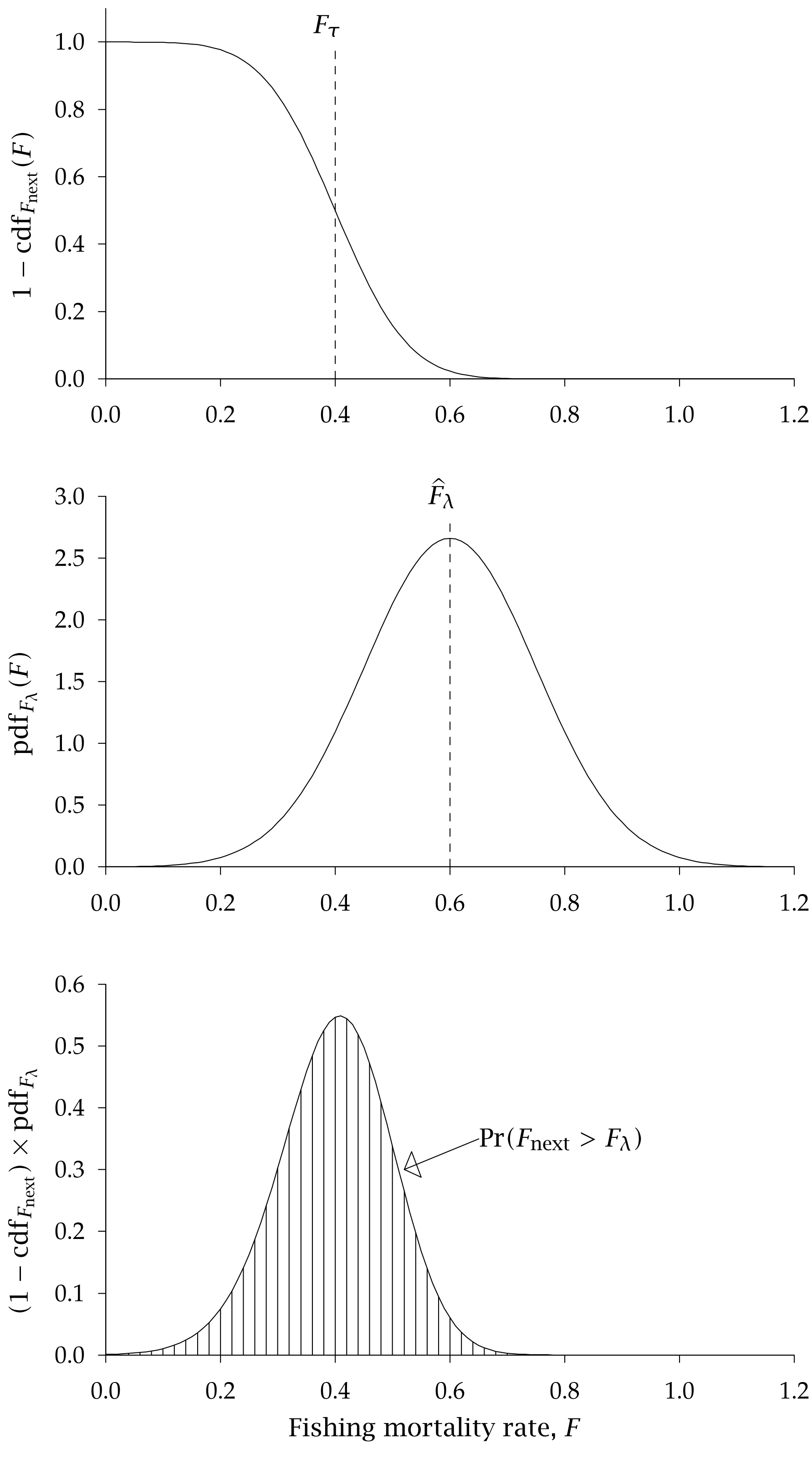
Figure 6. Contours of R_τ (dimensionless target reference point in F expressed as a proportion of current F) for North Atlantic swordfish, calculated using REPAST with normal uncertainties ($R_\lambda = 0.833$ with CV = 0.263). These computations are intended as an illustration, not an authoritative analysis of swordfish. Abbreviations and symbols are defined in Table 1.

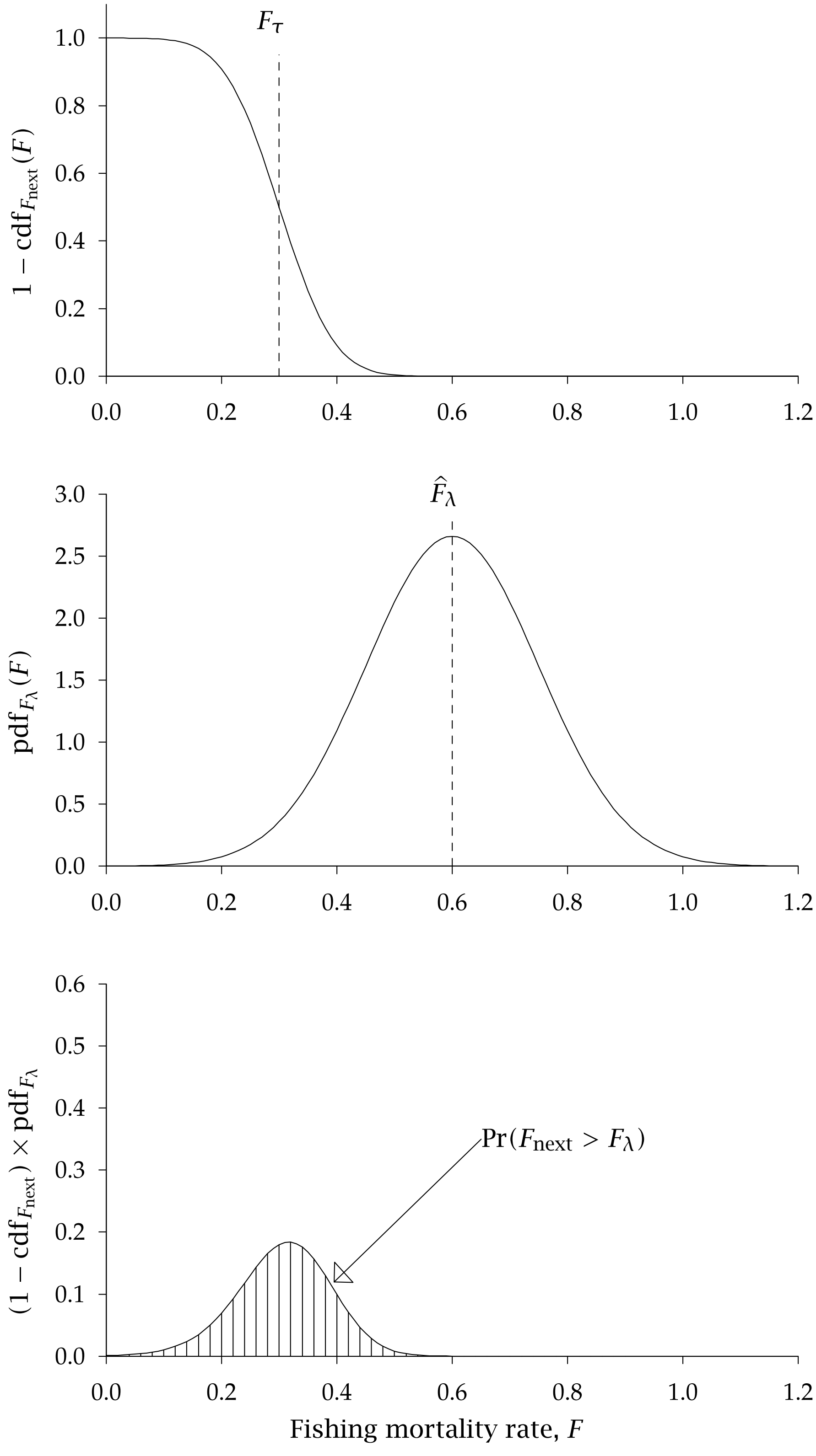
Figure 7. Solid line: empirical probability density of $R_\lambda = B_\lambda / B_{\mathrm{now}}$ from bootstrap fit of generalized production model to trimmed data on swordfish in north Atlantic Ocean. Dashed line: normal probability density with equal mean and SD, shown for comparison. Abbreviations and symbols are defined in Table 1.

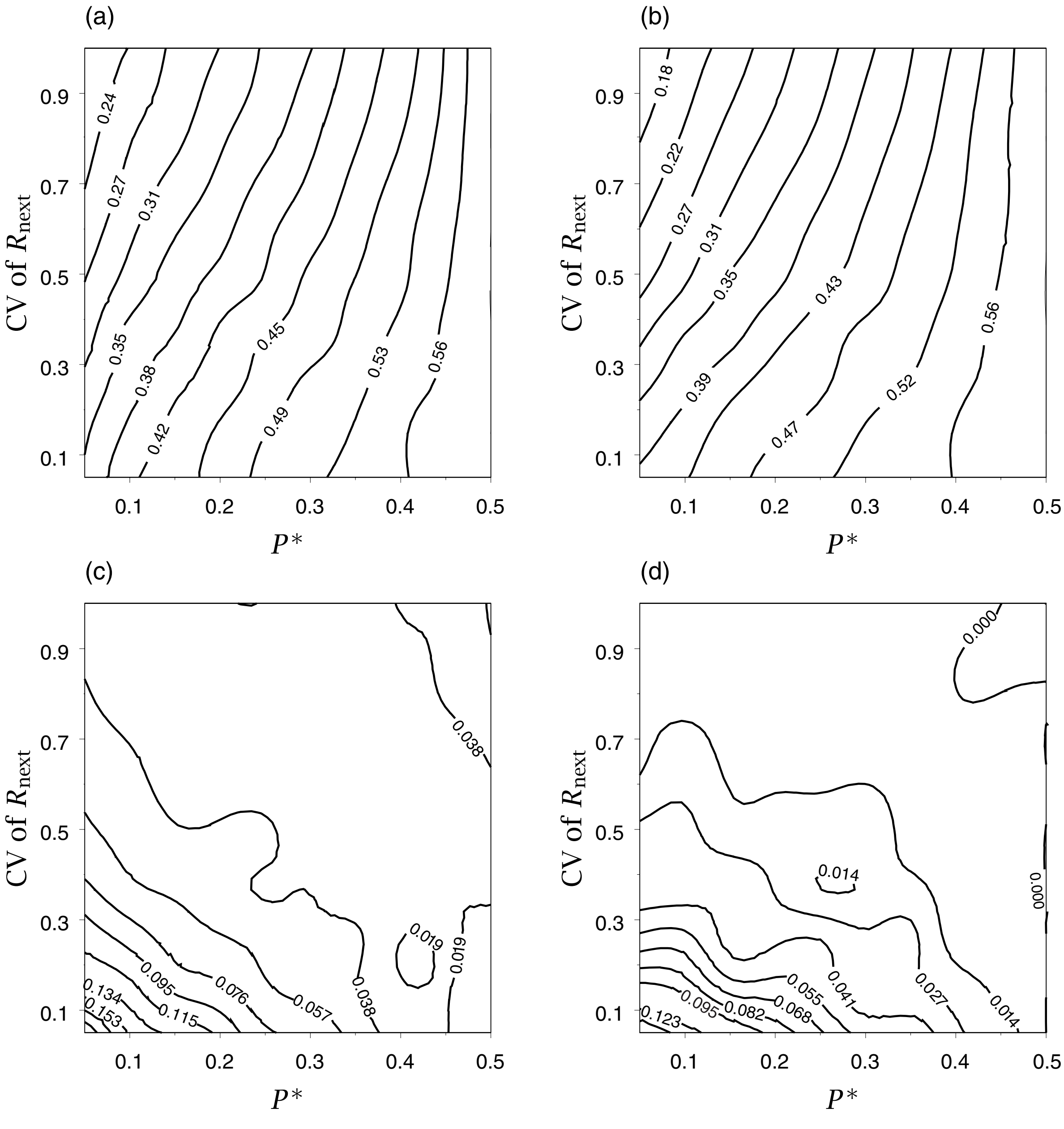
Figure 8. Contour of R_τ (dimensionless target reference point in biomass expressed as a proportion of current B) for North Atlantic swordfish, calculated using REPAST with normal uncertainties ($R_\lambda = 1.06$ with CV = 0.189). Contour lines are drawn at differing intervals. These computations are intended as an illustration, not an authoritative analysis of swordfish. Abbreviations and symbols are defined in Table 1.



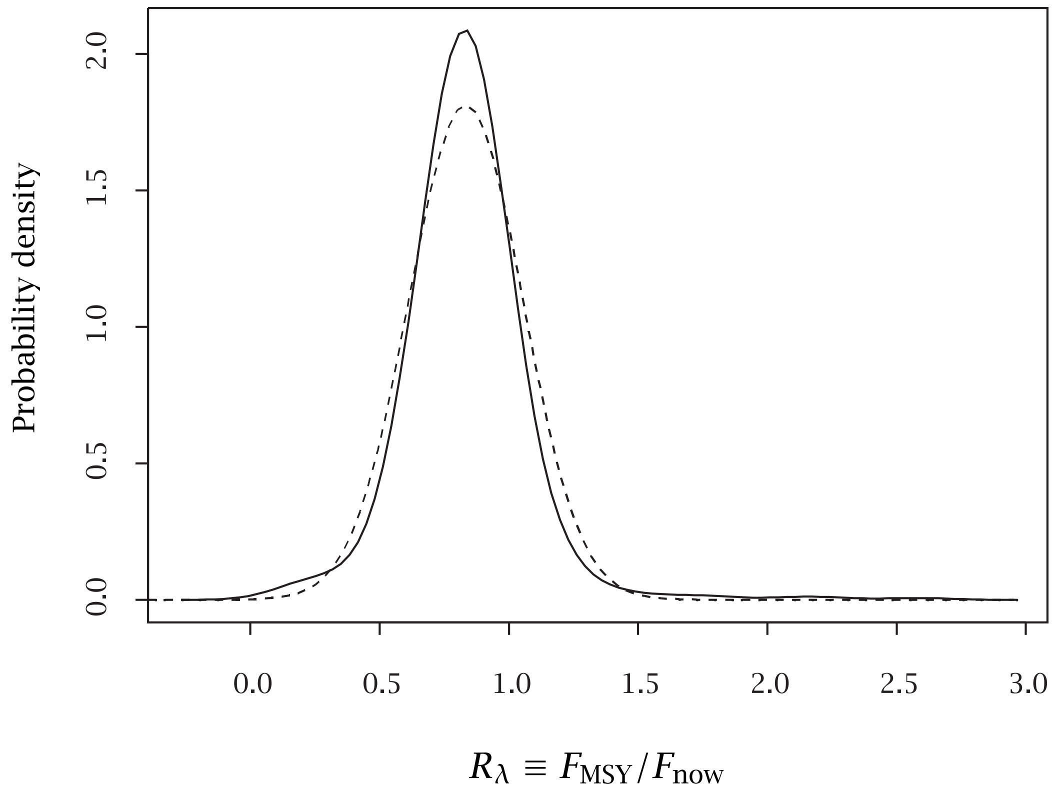
F_τ
F_λ
$P^* = \Pr(F_{next} > F_\lambda)$
Probability density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Fishing mortality rate in next period, F_{next}


F_τ
1.0
0.8
0.6
0.4
0.2
0.0
$1 - \mathrm{cdf}_{F_{\mathrm{next}}}(F)$
0.0
0.2
0.4
0.6
0.8
1.0
1.2
$\hat{F}_\lambda$
3.0
2.5
2.0
1.5
1.0
0.5
0.0
$\mathrm{pdf}_{F_\lambda}(F)$
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0.6
0.5
0.4
0.3
0.2
0.1
0.0
$(1 - \mathrm{cdf}_{F_{\mathrm{next}}}) \times \mathrm{pdf}_{F_\lambda}$
$\Pr(F_{\mathrm{next}} > F_\lambda)$
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Fishing mortality rate, F

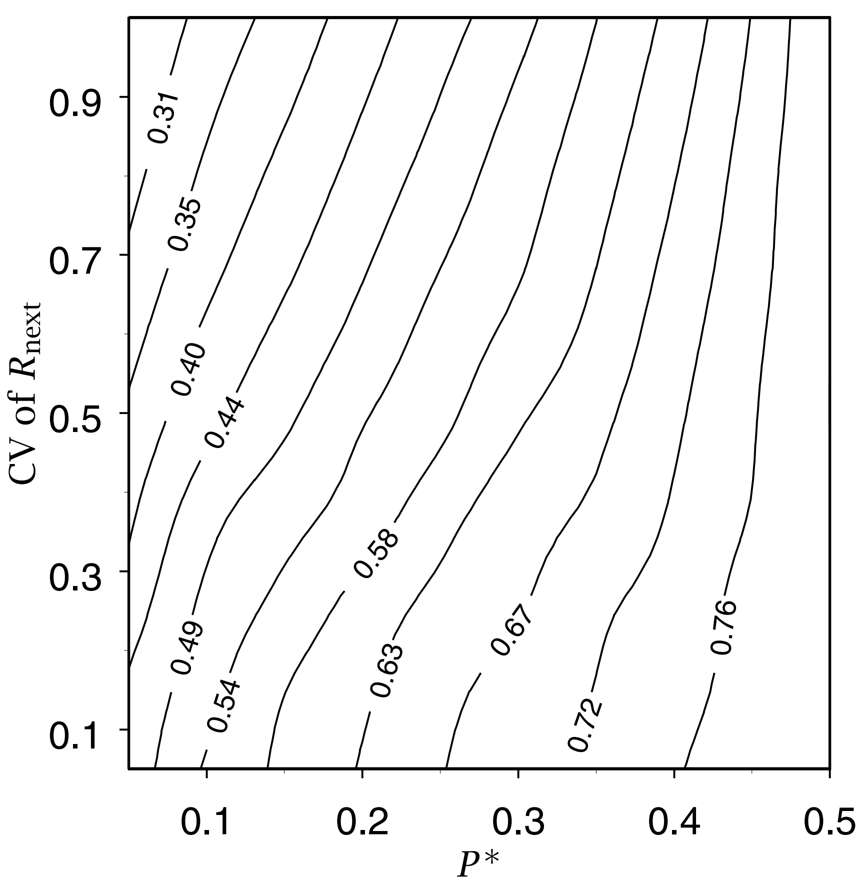

F_τ
$1 - \mathrm{cdf}_{F_{\mathrm{next}}}(F)$
1.0
0.8
0.6
0.4
0.2
0.0
0.0 0.2 0.4 0.6 0.8 1.0 1.2
$\hat{F}_\lambda$
$\mathrm{pdf}_{F_\lambda}(F)$
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0 0.2 0.4 0.6 0.8 1.0 1.2
$(1 - \mathrm{cdf}_{F_{\mathrm{next}}}) \times \mathrm{pdf}_{F_\lambda}$
$\Pr(F_{\mathrm{next}} > F_\lambda)$
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0 0.2 0.4 0.6 0.8 1.0 1.2
Fishing mortality rate, F



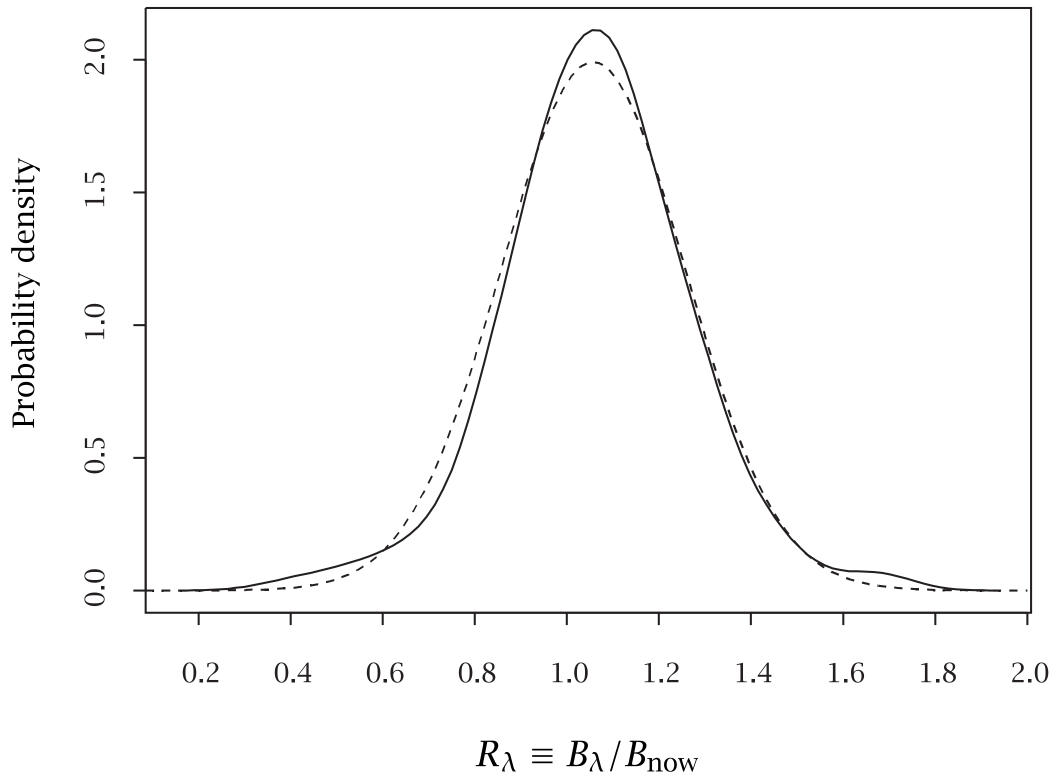
(a)
(b)
(c)
(d)
CV of R_{next}
P^*
0.1 0.2 0.3 0.4 0.5
0.1 0.3 0.5 0.7 0.9
0.24 0.27 0.31 0.35 0.38 0.42 0.45 0.49 0.53 0.56
0.18 0.22 0.27 0.31 0.35 0.39 0.43 0.47 0.52 0.56
0.038 0.019 0.019 0.038 0.057 0.076 0.095 0.115 0.134 0.153
0.000 0.014 0.000 0.014 0.027 0.041 0.055 0.068 0.082 0.095 0.123



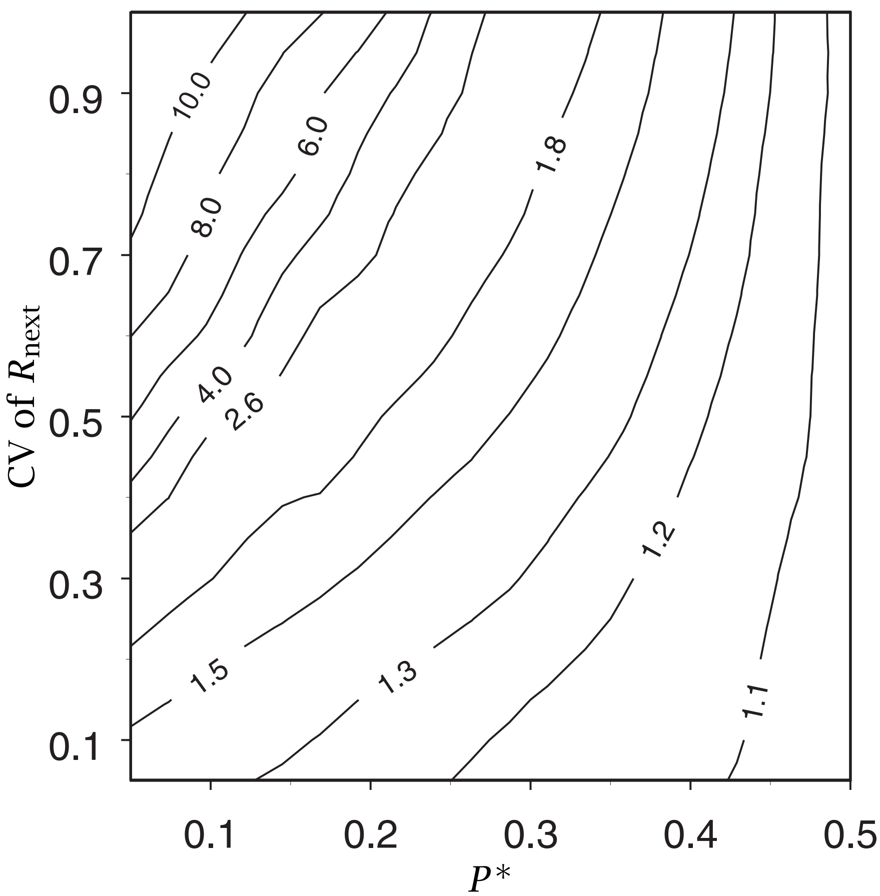
Probability density
0.0
0.5
1.0
1.5
2.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
$R_\lambda \equiv F_{\mathrm{MSY}}/F_{\mathrm{now}}$



0.9
0.7
0.5
0.3
0.1
CV of R_{next}
0.31
0.35
0.40
0.44
0.49
0.54
0.58
0.63
0.67
0.72
0.76
0.1
0.2
0.3
0.4
0.5
P^*



Probability density
0.0
0.5
1.0
1.5
2.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
$R_\lambda \equiv B_\lambda / B_{\mathrm{now}}$



10.0
8.0
6.0
4.0
2.6
1.8
1.5
1.3
1.2
1.1
0.9
0.7
0.5
0.3
0.1
CV of R_{next}
0.1
0.2
0.3
0.4
0.5
P^*